Natural Disasters and Human Capital Accumulation

Jesus Crespo Cuaresma

The empirical literature on the relationship between natural disaster risk and investment in education is inconclusive. Model averaging methods in a framework of cross-country and panel regressions show an extremely robust negative partial correlation between secondary school enrollment and natural disaster risk. This result is driven exclusively by geologic disasters. Exposure to natural disaster risk is a robust determinant of differences in secondary school enrollment between countries but not necessarily within countries Natural disasters, human capital, education, school enrollment, Bayesian model averaging. JEL codes: Q54, I20, E24, C11.

This article quantifies the effect of natural disaster risk on investments in education by exploiting both cross-country and time differences in school enrollment. Because of the large number of theories explaining differences in the rate of human capital accumulation across countries, model averaging techniques are used to explicitly take into account model uncertainty in extracting the effect of catastrophic risk on school enrollment.

The empirical literature on the economic effects of natural disasters has traditionally concentrated on the short-run effects of catastrophic events (for example, Dacy and Kunreuther 1969; Albala-Bertrand 1993a, b; Tol and Leek 1999; Rasmussen 2004; and Noy 2009). In contrast, Skidmore and Toya (2002) and Crespo Cuaresma, Hlouskova, and Obersteiner (2008)

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concentrate on long-run effects of disaster risk on the macroeconomy.[1] With the exception of some results in Skidmore and Toya, there has been no fully fledged empirical investigation of the effects of natural disasters on human capital accumulation across countries. This study aims to fill that gap. Case studies of individual economies have, however, examined the effect of natural disasters on educational attainment. Recently, Kim (2008) used data from the Demographic and Health Surveys and the Living Standard Measurement Study to examine empirically the effects of climate shocks on educational attainment in Burkina Faso, Cameroon, and Mongolia. Kim tends to find negative effects of disaster risk on secondary school completion.

From a theoretical perspective, the effect of natural disaster risk on educational investments is ambiguous. Skidmore and Toya (2002) argue that to the extent that natural catastrophes reduce the expected return to physical capital, rational individuals would shift their investment toward human capital.[2] But this is just one of the possible effects of natural disasters on human capital. One could also argue that, in a framework of models of agents with finite lives, the potential effect of natural disaster risk on mortality would lower education investment in disaster-prone countries. Checchi and García-Peñalosa (2004) present a simple theoretical model assessing the effect of production risk on education in which aggregate production risk determines the average level of education and its distribution. Checchi and García-Peñalosa show both theoretically and empirically that higher output volatility leads to lower educational attainment. If natural disaster risk is interpreted as a component of aggregate production risk in the economy, countries that are more affected by disasters should also exhibit lower levels of human capital accumulation, ceteris paribus.

These types of arguments stem from theoretical models and aim at unveiling the role of natural disaster risk as a determinant of cross-country differences. In this sense, these theoretical explanations refer to the long-run effects of natural disasters on education investments. Short-run effects on human capital accumulation associated with the actual occurrence of the disaster could be extremely important as well. Consider the 2005 earthquake in Pakistan. The Asian Development Bank and the World Bank (2005), estimated that 853 teachers and 18,095 students lost their lives in the disaster. More than 7,500 schools were affected by the earthquake, and the estimated reconstruction costs for education were the second highest by sector, after private housing. To the extent that reconstruction efforts are unable to restore capacity and education infrastructure after a disaster, long-run effects

1. See Okuyama (2009) for a review of the literature on assessing and measuring the economic effects of natural disasters.

2. Skidmore (2001) studies investment decisions under catastrophic risk, but the empirical results are based on a very reduced dataset.

may also emanate directly from the losses caused by the disaster. Natural disasters may also affect educational attainment through the effect of evacuations and school switching on the dropout rate and academic performance, as Sacerdote (2008) recently investigated using data from evacuations following hurricanes Katrina and Rita in New Orleans (see also Hanushek, Kain, and Rivkin 2004). The literature has also highlighted the effects on human capital investment related to loss of parents and to child labor decisions.

Ultimately, the question of how natural disaster risk affects human capital accumulation is an empirical one. Because a single theoretical framework cannot be relied on for explaining the link, an explicit assessment of model uncertainty is called for when quantifying the effect of natural disasters on education investments. This article uses Bayesian model averaging (BMA) to obtain robust estimates of the effect of disaster risk on secondary school enrollment rates (see Raftery 1995 and Clyde and George 2004, for general discussions of BMA and Fernández, Ley, and Steel 2001b and Sala-i-Martin, Doppelhofer, and Miller 2004 for applications to the identification of robust determinants of economic growth). Model averaging ensures that the results are not specific to the choice of model and take into the account not only the uncertainty of the estimates for a given model, but also the uncertainty in the choice of specification.

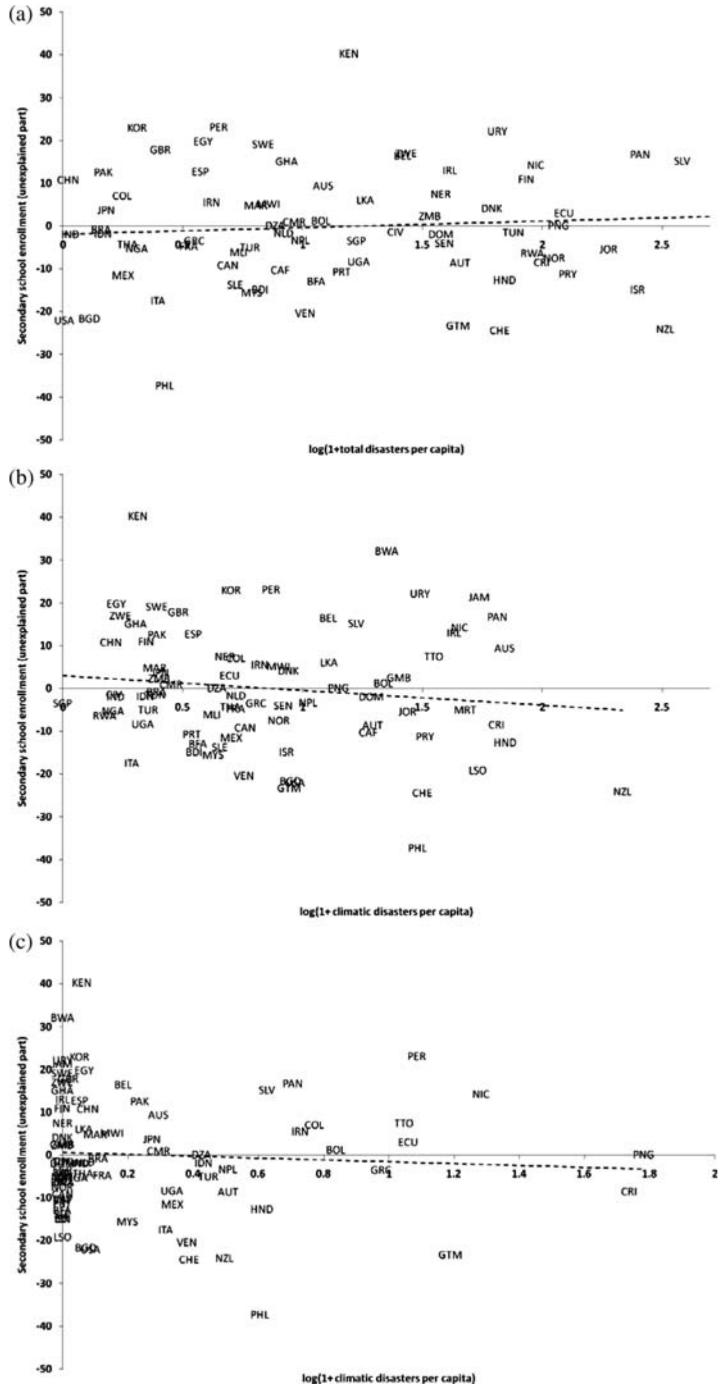
The results indicate that geologic disaster risk is a robust variable for explaining differences in secondary school enrollment rates across countries. The effect is sizable and well estimated. The school enrollment effect corresponding to the mean geologic disaster risk is around 1.65 percentage points in secondary school enrollment compared with a country with zero disaster risk. The maximum disaster risk-driven effect in the dataset implies approximately a 20 percentage point decrease in secondary school enrollment.

The article is structured as follows. Section I describes the empirical relationship between disaster risk and educational attainment. Section II describes BMA exercises to assess the robust effect of natural disaster risk as a determinant of differences in school enrollment rates in both a cross-section and a panel of countries. It also explicitly assesses subsample heterogeneity in the response of human capital accumulation to disaster risk. Section III summarizes the key findings.

I. A First Look At Education and Disasters

This section explores the relationship between natural disasters and human capital accumulation. Figure 1 presents scatterplots of average secondary school enrollment in 1980–2000 (after controlling for income per capita and geographic dummy variables based on world regions) against geologic and climate disasters and for all disasters combined for the 80 countries in the

FIGURE 1. Natural Disaster Risk and Secondary School Enrollment (unexplained part)



Source: Author's analysis based on data described in the text.

empirical analysis.[3] Climate-related catastrophes include floods, cyclones, hurricanes, ice storms, snow storms, tornadoes, typhoons, storms, wild fire, drought, and cold waves; geologic disasters include volcanic eruptions, natural explosions, avalanches, landslides, earthquakes, and wave surges. Following Skidmore and Toya (2002), figure 1 concentrates on a simple measure of natural disaster risk based on average disaster occurrence, here normalized by 1 million people. Disaster risk is thus measured as[4]

$$d_i = \log[1 + (\text{Number of disasters in country } i/\text{Population of country } i \text{ in millions})]. \quad (1)$$

Existing data on quantified losses and received aid are not used, since such measures are known to be plagued by endogeneity and other measurement problems. On the one hand, to the extent that disaster aid decisions are influenced by reported losses or number of people affected, governments would have an incentive to overreport these figures. On the other hand, a country's income level (which is highly correlated with human capital accumulation) is a basic determinant of the effectiveness of natural disaster risk management. Since successful risk management mechanisms will reduce the negative macroeconomic effects of disasters, using estimated losses could lead to a spurious negative correlation between disaster risk and education when the real correlation is between education and the reduction in natural disaster loss. Skidmore and Toya (2007), for instance, show that higher levels of education reduce the losses from natural disasters. The problems related to the use of reported losses from natural disasters have been noted in the recent comparative literature. Guha-Sapir and Below (2002) highlight some of these problems and conclude that existing datasets on the socioeconomic impact of disasters are unsatisfactorily defined and incomplete.

Vulnerability to natural disasters can be thought of as comprising risk exposure as well as the ability to cope with disaster shocks. The disaster variable used in this analysis proxies exclusively the first vulnerability component and thus is free of information on the ability to resist and recover from a natural disaster. Variables such as total estimated loss as a share of GDP or number of people injured or killed combine aspects of both vulnerability components. In this context, it would be difficult to argue that human capital does not affect the second component, the ability to cope with disaster shock. This would raise

3. The choice of countries is determined exclusively by data availability. The 80 countries in the scatterplot are those for which data on all variables used in the Bayesian model averaging analysis are available.

4. The source of disaster data is the Emergency Events Data Base (EM-DAT), which reports on catastrophic events that meet at least one of the following criteria: 10 or more people reported killed, 100 people reported affected, a call for international assistance was issued, or a state of emergency was declared (CRED 2004).

serious doubts about the empirical study unless good instruments were found to identify the exogenous component of disaster risk, a task that is extremely difficult in practice. Instead, the analysis concentrates on measures based on the frequency of disaster occurrence that do not contain information on the magnitude of the disaster, thus fulfilling the necessary condition of exogeneity.

Figure 1 shows a weak positive relationship between disaster risk and the education variable for total disasters, which disappears when the data are disaggregated into subgroups of climate and geologic disasters. Although the relationship is not statistically significant in any of the three cases reported in figure 1, this first glimpse at the relationship of interest seems to support the conclusions in Skidmore and Toya (2002) for the aggregated data.

To extract the pure effect of disaster risk on education investment, however, other variables that independently affect differences in educational attainment across countries must be controlled for. Learning about the pure impact of natural disasters on education implies formulating a potentially large model that hypothesizes that a human capital accumulation measure depends on a set of determinants and natural disaster risk. Obviously, the choice of extra controls for a model linking disaster risk to human capital accumulation depends on the theoretical setting. The literature presents many competing theories and effects to explain cross-country differences in educational attainment when assessing empirically the determinants of human capital accumulation. So that the empirical results do not depend on a specific theoretical (and thus econometric) specification or a particular choice of controls, BMA methods are used to investigate the robustness of disaster risk as a determinant of educational attainment in the framework of model uncertainty. Model averaging methods present a consistent framework to quantitatively assess model uncertainty when studying problems too ambiguous or theoretical complex to be convincingly represented by a single specification.

II. An Empirical Analysis of the Effect of Disaster Risk on Human Capital Accumulation

This section assesses natural disaster risk as a determinant of differences in school enrollment in both a cross-section and a panel of countries using BMA. It also assesses subsample heterogeneity in the response of human capital accumulation to disaster risk.

Model Uncertainty

The effect of catastrophic risk on human capital accumulation is estimated using linear econometric models of the type:

$$e_i = \alpha + \beta d_i + \sum_{j=1}^{K} \gamma_j x_j + \varepsilon_{i,}, \tag{2}$$

where e_i is a proxy for educational attainment, d_i is the disaster risk variable, $\mathbf{X} = (x_1 \ldots x_K)$ are other explanatory variables, and ε is a zero-mean error term with variance equal to σ^2. In Skidmore and Toya (2002), for instance, the initial level of the educational variable and income per capita are the only variables in the $\mathbf{X}$ set. Because numerous variables affect educational attainment, the aim is to obtain a measure that summarizes the effect of natural disaster risk on human capital accumulation after taking into account the degree of uncertainty embodied in specification (2) when the size of the model and the nature of the variables in $\mathbf{X}$ that belong to the model are unknown.

BMA presents a consistent framework for assessing the dimension of model uncertainty highlighted above.[5] Consider a set of $\bar{K}$ variables, $\mathbf{X}$ of which are potential determinants of educational attainment in a cross-country regression framework, so that the stylized specification considered is given by equation (2) for $K \leq \bar{K}$. In this situation, there are $2^{\bar{K}}$ possible combinations of regressors, each defining a model M_k. The Bayesian approach implies considering model specification itself as a quantity to be estimated. In this sense, it follows immediately that, by Bayes's theorem,

$$(3) \qquad P(M_k|\mathrm{Y}) = \frac{P(\mathrm{Y}|M_k)P(M_k)}{\sum_{m=1}^{2^{\bar{K}}} P(\mathrm{Y}|M_m)P(M_m)},$$

which indicates that the posterior probability of model M_k (the probability that the model is the true one given data Y) is related to its marginal likelihood, $P(\mathrm{Y} \mid M_k)$, and its prior probability, $P(M_k)$, as compared with the other models in the model space. Following Fernández, Ley, and Steel (2001a), an improper diffuse prior is set on α and σ, coupled with Zellner's (1986) g-prior on the parameter vector, which implies that

$$(4) \qquad P(\alpha, \beta, \gamma_j, \sigma|M_k) \infty \frac{1}{\sigma} N_{k+1}(0, \sigma^2(\mathrm{g}X_j'X_j)^{-1})$$

where N_{k+1} is a multivariate normal distribution of dimension $k+1$, and X_j is a matrix whose columns are given by the independent regressors in model M_k. This setting implies that the Bayes factor (ratio of marginal likelihoods) for two competing models, M_0 and M_1, is given by

$$(5) \qquad B_{1,0} = \frac{P(Y|M_1)}{P(Y|M_0)} = \left(\frac{\mathrm{g}}{\mathrm{g}+1}\right)^{(k_1-k_0)/2} \left(\frac{1+\mathrm{g}-R_1^2}{1+\mathrm{g}-R_0^2}\right)^{-(N-1)/2}$$

Where N is the sample size, k_j is the dimension of model j, and R_j^2 is the standard coefficient of determination for model j. Some particular values of g, the

5. Raftery (1995) and Clyde and George (2004) present general discussions of the use of BMA in linear regressions.

hyperparameter governing the prior over the slopes, have been systematically used in the literature. For $g = 1/N$ (the unit information prior), the Bayesian information criterion should be used in forming Bayes factors (see, for example, Kass and Wasserman 1995 and Kass and Raftery 1995), and thus BMA weights, while the risk inflation criterion (Foster and George, 1994) sets $g = 1/K^2$.[6]

$P(M_k|Y)$ can be used to build an estimate of the quantity of interest as, say, a weighted average of all estimates of β, where the weights are given by the posterior probability of each model from which the estimate was obtained,

$$E(\beta|Y) = \sum_k E(\beta|Y, M_k)P(M_k|Y). \tag{6}$$

Similarly, model averaged estimates of the posterior variance of β can be computed from the model averaged variance of the estimate, which in this setting summarizes information about the precision not only for a given model, but also across models.

While the method has been put forward in the setting of a cross-sectional dataset, it can be generalized to panel data in a straightforward fashion using the Frisch-Waugh-Lovell theorem. In particular, in models with cross-sectional fixed effects, the method can be applied to deviations of the mean for each cross-section (the within transformation) or to the mean of the cross-sections for each period when fixed period effects are assumed. The method is used here to estimate the effects of natural disaster risk on secondary school enrollment, which are robust to model uncertainty. In addition to the distribution of the estimated parameter, also of interest here is whether the data support the inclusion of natural disaster risk in specifications explaining differences in secondary school enrollment. This characteristic can be estimated by summing the posterior probability of the models containing the natural disaster variable, a statistic referred to as the posterior inclusion probability of the variable.

The Empirical Setting

A group of variables identified in the literature as important determinants of differences in human capital accumulation across countries are added as potential regressors in specification (2). The focus is on secondary school enrollment as the variable of interest, and thus the analysis aims to explain the flow of human capital (its accumulation) rather than its stock (which is usually measured by mean years of schooling). This focus is justified because primary schooling is compulsory in most countries in the sample and because the most important results for the issue under study were obtained using gross secondary school enrollment as the human capital variable (Skidmore and Toya 2002).

6. Fernández, Ley, and Steel (2001a) recommend using a benchmark prior based on the size of the group of potential regressors compared with sample size, so that $g = 1/\max(K^2,N)$.

Table 1 presents the regressors used in the BMA exercise. As potential explanatory variables, proxies for initial income (*y0*) and initial school enrollment (*e0*) account for wealth-induced human capital accumulation effects and for the observed persistence of human capital accumulation variables across and within countries and for their potential convergence across countries. National Gini coefficients capture differences in income distribution across economies, and the standard deviation of annual GDP growth rates is used as a proxy in analyzing the potential effect of macroeconomic instability. Life expectancy at birth in the initial period controls for differences in health. Credit constraints are included in the model using domestic credit to the private sector as a percentage of GDP as a proxy for financial depth.

The quality of political institutions is controlled for with the help of the Polity IV database, which offers a score variable (polity2) that quantifies a country's political system based on competitiveness and openness of executive recruitment, constraints on the chief executive, regulation, and competitiveness of participation. The polity2 measure ranges from −10 to +10, where −10 implies a strongly autocratic regime and +10 a strongly democratic regime. The models also control for war in a given country during the period under study.

TABLE 1. Variables and Definitions

Variable	Description	Source
e	Gross secondary school enrollment, average 1980–2000	World Bank 2006
e0	Initial gross secondary school enrollment, 1980	World Bank 2006
y0	Initial level of GDP per capita, 1980	World Bank 2006
gini	Gini index for income	World Bank 2006
life0	Life expectancy, 1980	World Bank 2006
vol	Volatility of GDP per capita growth	World Bank 2006
polity	Polity 2 indicator	Marshall and Jaggers 1995
pavroad	Percentage of paved roads	World Bank 2006
cred	Credit to private sector (percent of GDP)	World Bank 2006
area	Land area	World Bank 2006
popdens	Population density, 1980	World Bank 2006
inv	Investment in physical capital, 1980	Heston, Summers, and Aten 2006
war	Dummy variable for occurrence of war	—
laam	Dummy variable for Latin America and Caribbean	—
asia	Dummy variable for Asia and Pacific	—
safrica	Dummy variable for Sub-Saharan Africa	—
nafrica	Dummy variable for North Africa and Middle East	—
	Disaster risk, based on total disasters per million inhabitants	CRED 2004
	Disaster risk, based on climate disasters per million inhabitants	CRED 2004
	Disaster risk, based on geologic disasters per million inhabitants	CRED 2004

To control for the effect of country characteristics other than disaster risk on human capital investment, variables measuring total area and population density are included. Physical investment as a percentage of GDP is also considered as a potential determinant of human capital accumulation, to capture the complementarity or substitutability effects of physical and human capital. Regional dummy variables (for Asia and Pacific, Latin America and the Caribbean, North Africa and the Middle East, and Sub-Saharan Africa are added to the set of potential determinants of enrollment rates. The cross-country dataset contains data on all 80 countries for which all variables in table 1 are available.[7] Table 2 presents descriptive statistics for all variables over 1980–2000, as well as for the dataset divided into 10- and 5-year periods.

Several empirical studies of the determinants of schooling have used these variables in econometric models. Flug, Spilimbergo, Wachtenheim (1998), for instance, assess the effect of macroeconomic volatility on investment in education and present models that control for income inequality, credit market development, initial per capita income, and initial education levels. Some studies have noted the importance of social and political institutions as factors affecting human capital accumulation (Stijns 2006).

The results of the BMA exercise, obtained by averaging over the full model space, are presented in table 3.[8] Before the analysis, the variables were standardized by subtracting the mean and dividing by the standard deviation, so the resulting parameter estimates should be interpreted as the effect of increasing the variable by one standard deviation. The table reports the posterior inclusion probability of each variable computed as the sum of the posterior probability of the models including that variable plus the mean of the posterior distribution of the parameter attached to the variable and its standard deviation. The posterior inclusion probability can be interpreted as the probability that a given variable belongs to the true model. Explanatory variables are classified as robust if the probability that the variable belongs to the model increases is higher than the prior inclusion probability of the variable. For the BMA results in table 3, a diffuse prior was imposed over the model space, so

7. The countries in the sample are Algeria, Australia, Austria, Bangladesh, Belgium, Bolivia, Botswana, Brazil, Burkina Faso, Burundi, Cameroon, Canada, Central African Republic, China, Colombia, Costa Rica, Côte d'Ivore, Denmark, Dominican Republic, Ecuador, Egypt, El Salvador, Finland, France, Gambia, Ghana, Greece, Guatemala, Honduras, India, Indonesia, Iran, Ireland, Israel, Italy, Jamaica, Japan, Jordan, Kenya, Republic of Korea, Lesotho, Malawi, Malaysia, Mali, Mauritania, Mexico, Morocco, Nepal, Netherlands, New Zealand, Nicaragua, Niger, Nigeria, Norway, Pakistan, Panama, Papua New Guinea, Paraguay, Peru, Philippines, Portugal, Rwanda, Senegal, Sierra Leone, Singapore, Spain, Sri Lanka, Sweden, Switzerland, Thailand, Trinidad and Tobago, Tunisia, Turkey, Uganda, United Kingdom, United States, Uruguay, República Bolivariana de Venezuela, Zambia, and Zimbabwe.

8. In many other applications, the size of the model space renders the computation of all models intractable, and Markov Chain Monte Carlo methods tend to be used to reduce the number of models to be estimated.

TABLE 2. Descriptive Statistics

	Cross-country data					Ten-year panel					Five-year panel				
Variable	Mean	Median	Maximum	Minimum	Standard deviation	Mean	Median	Maximum	Minimum	Standard deviation	Mean	Median	Maximum	Minimum	Standard deviation
e	58.721	54.217	125.871	6.226	35.124	61.660	59.396	160.763	5.618	35.913	59.146	55.828	160.763	3.572	35.882
e0	44.919	38.777	104.812	2.697	30.285	49.592	43.370	119.509	2.697	31.483	52.942	47.527	142.488	2.697	33.520
y0	8.333	8.334	10.088	6.579	1.065	8.406	8.447	10.223	6.526	1.091	8.421	8.466	10.284	6.522	1.102
life0	61.118	61.920	76.092	35.403	11.138	62.378	65.614	78.837	0.000	12.532	63.481	66.417	79.531	35.196	11.401
vol	3.771	3.657	15.327	1.160	2.086	2.990	2.492	8.706	0.581	1.744	3.110	2.389	27.554	0.258	2.490
polity	1.088	1.500	10.000	−10.000	7.736	2.145	6.000	10.000	−10.000	7.588	2.671	6.000	10.000	−9.000	7.343
pavroad	45.039	39.567	100.000	4.657	27.264	45.568	45.808	100.000	4.300	26.471	45.504	45.808	100.000	4.300	26.095
gini	42.205	40.555	63.010	24.700	10.296	41.957	40.150	63.010	24.700	9.910	41.958	40.270	63.010	24.700	9.939
cred	35.935	29.135	122.146	0.965	25.990	41.100	30.873	175.731	0.000	33.361	41.872	30.683	180.509	0.965	34.805
area	0.979	0.296	9.327	0.001	2.100	0.930	0.294	9.327	0.001	1.997	0.972	0.296	9.327	0.001	2.063
popdens	0.132	0.045	3.603	0.002	0.408	0.131	0.054	4.084	0.002	0.363	0.139	0.052	4.548	0.002	0.423
inv	23.113	23.290	56.490	1.470	10.898	20.546	19.705	56.100	3.030	10.697	21.307	21.320	56.490	1.470	10.840
d_t	1.004	0.912	2.394	0.000	0.577	0.081	0.048	0.395	0.000	0.080	0.084	0.054	0.477	0.000	0.087
d_c	0.875	0.739	2.334	0.000	0.526	0.066	0.041	0.377	0.000	0.067	0.068	0.044	0.445	0.000	0.075
d_g	0.279	0.067	1.781	0.000	0.410	0.017	0.002	0.195	0.000	0.034	0.018	0.000	0.322	0.000	0.039

Source: Author's analysis based on data described in the text.

Table 3. Bayesian Model Averaging Results for Cross-section of Countries

	Total disasters			Climate disasters			Geologic disasters		
Variable	PIP	PM	PSD	PIP	PM	PSD	PIP	PM	PSD
eo	*0.999*	*0.609*	*0.074*	*0.999*	*0.610*	*0.076*	*0.999*	*0.615*	*0.077*
y0	*0.958*	*0.259*	*0.096*	*0.859*	*0.191*	*0.106*	*0.880*	*0.202*	*0.106*
life0	*0.716*	*0.15*	*0.12*	*0.934*	*0.237*	*0.102*	*0.920*	*0.228*	*0.104*
vol	0.195	−0.00	0.022	0.184	−0.00	0.022	0.201	−0.00	0.024
polity	0.158	0.005	0.021	0.108	0.000	0.013	0.108	0.000	0.013
pavroad	0.150	−0.00	0.014	0.145	−0.00	0.014	0.140	−0.00	0.014
gini	0.127	0.002	0.018	0.117	0.001	0.016	0.122	0.002	0.017
cred	0.891	−0.10	0.053	0.815	−0.09	0.057	*0.840*	*−0.09*	*0.057*
war	0.149	0.004	0.016	0.122	0.002	0.012	0.119	0.001	0.012
area	0.13	0.002	0.012	0.153	0.004	0.015	0.148	0.003	0.014
popdens	0.35	−0.01	0.029	0.24	−0.01	0.023	0.274	−0.01	0.026
inv	0.138	0.003	0.014	0.136	0.003	0.014	0.136	0.003	0.014
safr	*0.567*	*−0.07*	*0.080*	0.265	−0.02	0.061	0.264	−0.02	0.060
nafr	0.174	0.004	0.020	0.170	0.004	0.019	0.164	0.003	0.018
asia	0.224	−0.01	0.037	0.250	−0.01	0.042	0.234	−0.01	0.041
laam	*0.945*	*−0.12*	*0.051*	*0.996*	*−0.15*	*0.043*	*0.987*	*−0.14*	*0.047*
total disasters, d_t	0.318	−0.01	0.033	—	—	—	—	—	—
clim. disasters, d_c	—	—	—	0.134	−0.00	0.015	—	—	—
geol. disasters d_g	—	—	—	—	—	—	*0.868*	*−0.08*	*0.049*
g-prior		BIC			BIC			BIC	
Prior model size		8.5			8.5			8.5	
Number of observations		80			80			80	
Number of models		131,072			131,072			131,072	

PIP is posterior inclusion probability, PM is posterior mean, PSD is posterior standard deviation, and BIC is Bayesian information criterion.

Note: Values in italics have a PIP higher than 0.5.

Source: Author's analysis based on data described in the text.

that $P(M_f) = 1/2^{\bar{K}}$ for all f, implying an average prior model size of $\bar{K}/2$ and a prior inclusion probability of 0.5 for each regressor.

The results in table 3 include a group of regressors with a different natural disaster risk proxy in each set of covariates (all disasters, climate disasters, and geologic disasters). The initial educational attainment variable and the initial per capita income are highly robust in explaining secondary education enrollment. The parameter attached to initial educational attainment is estimated very precisely, and its posterior distribution has a mean below unity, implying (conditional) convergence in secondary school enrollment levels across countries. Initial income level and life expectancy also appear as robust determinants of school enrollment, with positive effects that are estimated with good precision. The regional dummy variables for Latin American countries is robust and negatively related to school enrollment, while that for Sub-Saharan Africa is marginally robust in one of the two settings. The results for the credit variable, which are robust but negatively related to school enrollment, are surprising and counterintuitive; they seem to be caused by the credit variable's high correlation with the regional dummy variables. In other settings that excluded the regional dummy variables and single variables, the credit variable was no longer robust, while all other results were unchanged. The effects of the other nondisaster variables were neither robust in posterior inclusion probability nor estimated with precision.

The results for the natural disaster risk variables shed light on the channels between human capital accumulation and catastrophic risk. When data on all disasters or climate disasters are used, the implied risk levels do not appear to be robustly linked to school enrollment. For geologic disasters, however, the risk variable is robust and negatively linked to educational attainment, and the effect is well estimated, with a ratio of posterior mean to posterior standard deviation of around 1.7.[9] The results imply that the decline in secondary school enrollment for the mean country associated with geologic disaster risk is around 2.13 percentage points higher than that for a country with zero disaster risk. The maximum disaster risk–driven effect implies an approximately 13.6 percentage point decline in secondary school enrollment.

Table 4 shows the results for the estimated models with the highest posterior probability. The setting with geologic disasters as the natural disaster risk variable belongs to the best model for posterior probability, which would have been the chosen specification had model selection been used instead of model

9. Although the ratio of the posterior mean to the posterior standard deviation is often used as a measure of precision in estimating the effect of an independent variable on the dependent variable, the usefulness of this statistic depends on the shape of the posterior distribution of the corresponding parameter. This is more the case if posterior distributions based on the full model space (and thus with a mass point at zero) are used instead of those computed using only models that include a given variable. Results that concentrate only on models including a given variable are not qualitatively different from those presented here (available from the author on request).

Table 4. Single Specifications with Highest Posterior Probability

Variable	Best model 1[a]	Best model 2[b]
Intercept	0.000 (0.028)	0.000 (0.027)
e0	0.598*** (0.068)	0.594*** (0.066)
y0	0.227*** (0.069)	0.261*** (0.068)
life	0.257*** (0.074)	0.240*** (0.072)
cred	−0.11*** (0.040)	−0.12*** (0.039)
laam	−0.15*** (0.031)	−0.11*** (0.034)
Geolog. disasters	—	−0.07** (0.032)
Adjusted R^2	0.936	0.940
Obs.	80	80

*** Significance at the 1 percent level; **significant at the 5 percent level.

Note: Numbers in parentheses are standard errors.

a. Model with the highest posterior probability in the Bayesian model averaging (BMA) setting corresponding to columns 1 and 2 in table 2.

b. Model with the highest posterior probability in the BMA setting corresponding to column 3 in table 2.

Source: Author's analysis based on data described in the text.

averaging. In this specification, the effect of geologic disaster risk on enrollment is negative and significant.

Climate and geologic disasters have several differential characteristics that can be helpful in understanding and interpreting the results of the BMA analysis. Climate disasters, which tend to occur at regular intervals, are more predictable than geologic disasters, and their damage tends to be linked to physical capital, whereas geologic disasters affect primarily human lives.[10] While economists have traditionally discussed the economic impact of natural disaster risk in terms of behavioral effects (related to the discounting of future utility or income) in the framework of theoretical models, several other channels link natural disaster risk to educational attainment on both the supply and demand sides. Damage to schools and other infrastructure, and teacher casualties, are obvious factors affecting the supply of education in the aftermath of a natural disaster. On the demand side, in addition to the potential indirect channels linking natural disaster risk with educational attainment through income, several studies show that children who lose a parent tend to have lower investment in human capital, after controlling for other differences (see Gertler, Levine, and Ames 2004). In this sense, the results can be interpreted as supporting the belief that the effects of natural disasters on human capital accumulation work through increased mortality risk. Apart from the fact that human losses affect educational attainment at the aggregate level through the increased mortality of educated individuals in disaster-prone countries, human losses also

10. Skidmore and Toya (2002) interpret the climate disaster group as proxying risks related to physical capital and the geologic disaster groups as proxying risks related to human life.

have an effect on child labor decisions, in particular since empirical results show that child labor is used to counteract short-run income shocks to the household (see Duryea, Lamb, and Levison 2007 for evidence from Brazil).

Education and Disasters: Panel Setting

The results indicate that natural disaster risk is a robust variable for explaining differences in secondary school enrollment across countries. The question naturally arises whether these effects are also observable within countries. Does the occurrence of a natural disaster reduce schooling rates immediately, so that the effect captured in the econometric analysis is a direct consequence of the disaster? Variation in disaster risk within countries could provide information on the direct effect of disasters instead of the effect of ex ante disaster risk. Thus, a clearer picture of the differential effect of disaster risk and disaster incidence might be obtained by complementing the cross-country results with time variation in disaster incidence.

To assess this possibility, the analysis was conducted again, this time using two panels based on 5- and 10-year subperiods. Because of the dynamic nature of the specification (the lagged dependent variable is potentially part of the model), estimation using country fixed effects would lead to biased estimates. Instead, the model is estimated based on the pooled dataset using period fixed effects.

$$e_{it} = \alpha + \beta d_{it} + \sum_{j=1}^{K} \gamma_j x_{jt} + \varepsilon_{it,}, \tag{7}$$

$$\varepsilon_{it} = \lambda_t + \nu_{it}, \tag{8}$$

where the error term ε_{it}, can now be decomposed into a fixed time effect common to all countries (λ_t), which summarizes common shocks to the education variable, and the usual error term with constant variance (υ_{it},).

The results reveal that the robust negative effect of natural disaster risk on human capital accumulation found in the cross-country regressions disappears when the focus is exclusively on shorter run variation in school enrollment (table 5). Although the sign of the parameter for geologic disasters remains negative, it is estimated with low precision and has an inclusion probability below 0.5. The inclusion probability of the disaster variables, particularly the geologic disaster variable, increases as the horizon under consideration moves toward long-run comparisons. These results provide an interesting insight into the determinants of human capital accumulation in the short and medium runs. The posterior inclusion probabilities of the variables for the 5-year panel show that, apart from the natural persistence of human capital accumulation variables, only income is an important determinant of secondary school enrollment rate differences. For the 10-year panel, life expectancy appears as an additional robust variable in explaining schooling differences.

Table 5. Bayesian Model Averaging Results for Panel Setting

Variable	PIP	PM	PSD	PIP	PM	PSD	PIP	PM	PSD
Five-year panel									
eo	*0.999*	*0.844*	*0.039*	*0.999*	*0.848*	*0.038*	*0.999*	*0.848*	*0.038*
y0	*0.899*	*0.114*	*0.052*	*0.897*	*0.112*	*0.051*	*0.896*	*0.112*	*0.052*
life0	0.177	0.012	0.033	0.173	0.011	0.032	0.174	0.012	0.032
vol	0.062	−0.00	0.004	0.062	−0.00	0.004	0.062	−0.00	0.004
polity	0.262	0.011	0.022	0.218	0.008	0.019	0.221	0.008	0.019
pavroad	0.068	−0.00	0.004	0.068	−0.00	0.004	0.068	−0.00	0.004
gini	0.067	−0.00	0.005	0.069	−0.00	0.005	0.068	−0.00	0.005
cred	0.078	−0.00	0.007	0.076	−0.00	0.007	0.076	−0.00	0.007
war	0.072	−0.00	0.005	0.074	−0.00	0.005	0.074	−0.00	0.005
area	0.290	0.008	0.015	0.311	0.009	0.016	0.309	0.009	0.016
popdens	0.085	−0.00	0.007	0.082	−0.00	0.006	0.082	−0.00	0.006
inv	0.115	0.002	0.010	0.117	0.002	0.010	0.117	0.002	0.010
safr	0.114	−0.00	0.013	0.099	−0.00	0.012	0.099	−0.00	0.012
asia	0.077	0.000	0.006	0.075	0.000	0.006	0.075	0.000	0.006
laam	0.182	−0.00	0.013	0.206	−0.00	0.014	0.202	−0.00	0.014
nafr	0.182	0.004	0.012	0.170	0.004	0.012	0.169	0.004	0.011
total disasters, d_t	0.300	−0.00	0.016	—	—	—	—	—	—
clim. disasters, d_c	—	—	—	0.061	0.000	0.004	—	—	—
geol. disasters d_g	—	—	—	—	—	—	0.081	−0.00	0.005
g-prior		BIC			BIC			BIC	
Prior model size		8.5			8.5			8.5	
Number of observations		292			292			292	
Number of models		131,072			131,072			131,072	
Ten-year panel									
eo	*0.999*	*0.610*	*0.082*	*0.999*	*0.609*	*0.082*	*0.999*	*0.610*	*0.082*
y0	*0.900*	*0.232*	*0.111*	*0.902*	*0.233*	*0.111*	*0.900*	*0.232*	*0.111*
life0	*0.554*	*0.077*	*0.084*	*0.550*	*0.076*	*0.084*	*0.554*	*0.077*	*0.084*

(Continued)

TABLE 5. Continued

Variable	PIP	PM	PSD	PIP	PM	PSD	PIP	PM	PSD
vol	0.104	−0.00	0.018	0.104	−0.00	0.018	0.104	−0.00	0.018
polity	0.273	0.022	0.045	0.263	0.021	0.044	0.273	0.022	0.045
pavroad	0.124	−0.00	0.014	0.124	−0.00	0.015	0.124	−0.00	0.014
gini	0.097	0.000	0.015	0.098	0.000	0.015	0.097	0.000	0.015
cred	0.098	−0.00	0.016	0.098	−0.00	0.016	0.098	−0.00	0.016
war	0.107	−0.00	0.013	0.106	−0.00	0.013	0.107	−0.00	0.013
area	0.339	0.021	0.035	0.345	0.021	0.035	0.339	0.021	0.035
popdens	0.095	−0.00	0.016	0.094	−0.00	0.016	0.095	−0.00	0.016
inv	0.094	0.001	0.014	0.094	0.001	0.014	0.094	0.001	0.014
safr	0.191	−0.01	0.043	0.192	−0.01	0.043	0.191	−0.01	0.043
asia	0.130	0.001	0.021	0.131	0.001	0.021	0.130	0.001	0.021
laam	0.324	−0.02	0.041	0.340	−0.02	0.042	0.324	−0.02	0.041
nafr	0.241	0.013	0.031	0.241	0.013	0.031	0.241	0.013	0.031
total disasters, d_t	0.156	−0.00	0.019	—	—	—	—	—	—
clim. disasters, d_c	—	—	—	0.088	0.000	0.010	—	—	—
geol. disasters d_g	—	—	—	—	—	—	0.156	−0.00	0.019
g-prior		BIC			BIC			BIC	
Prior model size		8.5			8.5			8.5	
Number of observations		292			292			292	
Number of models		131,072			131,072			131,072	

PIP is posterior inclusion probability, PM is posterior mean, PSD is posterior standard deviation, and BIC is Bayesian information criterion.

Note: Values in italics have a PIP higher than 0.5. All models include period fixed effects.

Source: Author's analysis based on data described in the text.

The models were also estimated using country and period fixed effects, but excluding the initial level of schooling from the pool of potential explanatory variables. The results are unchanged for natural disaster risk but differ for other explanatory variables. In particular, the BMA estimate of the effect of credit to the private sector is very robust and positively related to schooling, implying that credit constraints have a strong influence on medium-run human capital accumulation dynamics. A comparison of this result to the previous estimates implies that credit constraints are a robust determinant of schooling within countries but not necessarily across countries. These results complement those of Flug, Spilimbergo, and Wachtenheim (1998).[11]

Parameter Heterogeneity and Interaction Effects

An important question is whether the effect of natural disaster risk on human capital accumulation depends on other country characteristics. Studies have found that the effects of natural disaster risk on several macroeconomic variables are modulated by institutional and economic factors. Noy (2009) shows that the GDP costs depend on the strength of a country's institutions, as well as on the level of income per capita. Similarly, Crespo Cuaresma, Hlouskova, and Obersteiner (2008) find that the potential positive effects of disasters on technology imports exist only for more developed countries, not for poor economies. The usual approach to assessing heterogeneity in elasticities is to include interaction terms. In this case, the class of models considered for the cross-country case is given by

$$e_i = \alpha + \beta d_i + \eta d_i z_i + \sum_{j=1}^{K} \gamma_j x_j + \varepsilon_{i,}, \tag{9}$$

where variable z (in this case, $z \in \mathbf{X}$, although that need not be so in all cases) is responsible for explaining differences in the elasticity of school enrollment to disaster risk.

There is some debate in the literature on how to treat interaction terms in the framework of variable selection and BMA. While some analysts include the interaction as an extra linear covariate in the model, without setting any particular prior structure on models including the product of variables (see Masanjala and Papageorgiou 2008), others provide special treatment to models with interaction terms (see Chipman 1996 for a general discussion and Crespo Cuaresma, Doppelhofer, and Feldkircher 2008 and Crespo Cuaresma forthcoming for applications).

The main problem in interpreting BMA results when the interaction term is considered a standard variable and the model averages over all possible combinations of variables is that some estimates will be based on models that include the interaction terms but do not specify the main effect of the interacted

11. The detailed results are available from the author.

variables (the "parent variables"). This can lead to improper interpretation of the interaction effect, since the absence of the parent variables in the specification implies that the interaction term may actually be capturing the direct effect of one or both of the parent variables. In this sense, if the aim is to fulfill Chipman's (1996) strong heredity principle, only models that include both the interaction term and the parent terms should be considered. For instance, in a more general setting, with standard variables and an interaction term (consisting of variables from the former group), standard BMA would imply averaging over all possible combinations of these variables. But the strong heredity principle requires excluding model specifications that include the interaction term without the parent variables, which means that $2^{K\text{-}1} + 2^{K\text{-}3}$ models would be evaluated.

Both approaches are applied to the dataset to evaluate the existence of subsample heterogeneity in the effects of natural disaster risk on human capital. Different model spaces are evaluated, each containing potential interactions of the disaster variable with the initial level of school enrollment, the level of income per capita, the political regime, and the degree of credit constraint. Thus, BMA estimates are alternatively obtained for model spaces defined by the specification in equation (9) with the interaction variable z given by each one of these covariates. Table 6 presents the posterior inclusion probability, posterior mean, and posterior standard deviation for the interaction terms for model spaces comprising all combinations of all possible variables plus the interaction term and for model spaces respecting the strong heredity principle.[12] Several interesting results emerge. There is little evidence for robust heterogeneous effects of natural disasters on education. In the results obtained by imposing the strong heredity principle, the only interaction with a posterior inclusion probability higher than 0.5 is for the combined effect of geologic disasters and political regime (*polity*) in the cross-section setting. The BMA estimate indicates that, ceteris paribus, school enrollment is more sensitive to natural disasters in democratic countries. A similar negative effect is found in the 10-year panel using the standard BMA prior across models instead of the strong heredity prior.

Other Robustness Checks

Other robustness checks were also performed to ensure that the results are not driven by the prior structure imposed on the BMA procedure. The results are robust to changing the parameter prior from the unit information prior to the risk inflation criterion as well as to the use of a hyperprior on model size as proposed by Ley and Steel (2009). For the cross-country setting, BMA was conducted on an alternative set of covariates, enlarging the group of explanatory

12. Complete results for all other variables are available from the author. The results presented in previous sections are not qualitatively affected by the inclusion of the interaction terms as extra variables.

TABLE 6. Bayesian Model Averaging Results for Interaction Terms

	Standard Bayesian model averaging			Strong heredity prior[a]		
Variable	PIP	PM	PSD	PIP	PM	PSD
Cross-section of countries						
Total disasters * *eo*	0.314	−0.02	0.048	0.048	−0.00	0.023
*Clim. disasters * eo*	0.185	−0.01	0.031	0.025	−0.00	0.018
*Geol. disasters * eo*	0.266	−0.01	0.039	0.095	0.000	0.020
*Total disasters * y0*	0.371	−0.05	0.154	0.122	−0.05	0.180
*Clim. disasters * y0*	0.155	−0.01	0.069	0.031	−0.00	0.072
*Geol. disasters * y0*	*0.636*	*−0.18*	*0.337*	0.336	−0.25	0.443
*Total disasters * polity*	0.475	−0.05	0.080	0.140	−0.01	0.044
*Clim. disasters * polity*	0.180	−0.00	0.028	0.026	−0.00	0.010
*Geol. disasters * polity*	*0.951*	*−0.11*	*0.045*	*0.736*	*−0.07*	*0.059*
*Total disasters * cred*	*0.878*	*−0.11*	*0.057*	0.186	−0.01	0.042
*Clim. disasters * cred*	*0.624*	*−0.06*	*0.062*	0.467	−0.06	0.076
*Geol. disasters * cred*	*0.624*	*−0.06*	*0.060*	0.268	−0.03	0.064
Five-year panel						
*Total disasters * eo*	0.069	−0.00	0.005	0.005	0.000	0.002
*Clim. disasters * eo*	0.061	0.000	0.005	0.003	−0.00	0.002
*Geol. disasters * eo*	0.179	−0.00	0.012	0.018	−0.00	0.004
*Total disasters * y0*	0.081	0.000	0.005	0.004	−0.00	0.002
*Clim. disasters * y0*	0.061	−0.00	0.009	0.003	−0.00	0.008
*Geol. disasters * y0*	0.269	−0.01	0.053	0.028	−0.00	0.058
*Total disasters * polity*	0.102	−0.00	0.009	0.003	−0.00	0.002
*Clim. disasters * polity*	0.064	0.000	0.004	0.000	−0.00	0.000
*Geol. disasters * polity*	0.483	−0.02	0.026	0.044	−0.00	0.017
*Total disasters * cred*	0.164	−0.00	0.012	0.000	−0.00	0.001
*Clim. disasters * cred*	0.107	−0.00	0.008	0.000	−0.00	0.001
*Geol. disasters * cred*	0.168	−0.00	0.011	0.001	−0.00	0.000
Ten-year panel						
*Total disasters * eo*	0.142	−0.00	0.022	0.014	−0.00	0.010
*Clim. disasters * eo*	0.093	−0.00	0.015	0.009	−0.00	0.009
*Geol. disasters * eo*	0.399	−0.03	0.045	0.068	−0.00	0.020
*Total disasters * y0*	0.153	−0.00	0.015	0.014	−0.00	0.009
*Clim. disasters * y0*	0.089	−0.00	0.030	0.007	−0.00	0.027
*Geol. disasters * y0*	*0.527*	*−0.14*	*0.338*	0.182	−0.16	0.433
*Total disasters * polity*	0.143	−0.00	0.025	0.007	−0.00	0.007
*Clim. disasters * polity*	0.090	0.000	0.013	0.002	−0.00	0.002
*Geol. disasters * polity*	*0.592*	*−0.06*	*0.061*	0.089	−0.00	0.036
*Total disasters * cred*	0.223	−0.01	0.028	0.002	−0.00	0.004
*Clim. disasters * cred*	0.154	−0.00	0.022	0.001	−0.00	0.004
*Geol. disasters * cred*	0.205	−0.01	0.027	0.006	−0.00	0.003

PIP is posterior inclusion probability, PM is posterior mean, and PSD is posterior standard deviation.

Note: Values in italics have a PIP higher than 0.5.

a. Bayesian model averaging using only models that include the parent variables of the interaction terms.

Source: Author's analysis based on data described in the text.

variables in table 1 by an extra variable that measures the percentage of mountainous terrain in the countries. This variable controls for geographic and topographic effects that may be correlated with the disaster risk variables but that exert an independent effect on human capital investment (for instance, by affecting the return of infrastructure in terms of providing access to schools and thus affecting school enrollment). The BMA results for the importance and size of the effect of geologic disaster risk were essentially unchanged, while the mountainous terrain variable achieved a low posterior inclusion probability.

To assess the impact of influential observations, BMA parameters and inclusion probabilities were estimated based on subsamples. The results for the long-run effects of geologic disaster risk on secondary school enrollment rates are robust to the following changes in the dataset:

- Excluding the observations for disasters with the highest ratio of affected individuals per square kilometer (so as not to reduce the estimation sample dramatically, the cut-point was set at percentiles of the distribution of affected people by area ranging from the 80th to the 95th).
- Excluding the observations for the poorest countries in the sample (thresholds based on observed income levels ranging up to the 30th percentile were tried).
- Excluding the observations for zero disasters, so that the results are not driven exclusively by the differences between observations with zero disaster risk and those with a positive disaster risk.
- Excluding the five observations identified as outliers through inspection of the residuals of the specification that includes all potential variables. This change intensifies the effect of disasters on schooling, with the geologic disaster variable achieving even higher posterior inclusion probability and a higher estimated effect in absolute value.
- Allowing for differential effects in developed and developing countries. In this case, there is strong evidence of homogeneity of the effect across subsamples.

III. Conclusions

The effects of natural disaster risk on human capital accumulation have received little attention in the academic literature. This article offers a first, fully fledged empirical study of the effects of natural disasters on secondary school enrollment across countries. To avoid reaching conclusions that are driven by single specifications, Bayesian model averaging techniques were used to assess the robustness and size of the effects of natural disaster risk on human capital accumulation.

The results offer strong evidence of the negative effects of geologic natural disaster risk on secondary school enrollment rates and complement the case study literature. The effects tend to be homogeneous across countries and do not depend on income or the degree of human capital accumulation within a country. The empirical results presented here are robust to numerous variations in setting.

The evidence presented in this article unveils a negative effect of natural disaster risk that had hitherto been largely ignored in the academic literature. Further research on the issue should concentrate on isolating empirically the channels leading to the aggregate effect of disasters on educational attainment found in this analysis.

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